Environmental Modelling & Software 110 (2018) 129–138

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

A semantic multi-criteria approach to evaluate different types of energy generation technologies

Miriam Martínez-García [a, *], Aida Valls [a], Antonio Moreno [a], Arantza Aldea [b]

[a] Departament d'Enginyeria Informàtica i Matemàtiques, Universitat Rovira i Virgili, 43007 Tarragona, Spain
[b] Department of Computing and Communication Technologies, Oxford Brookes University, OX33 1HX Oxford, UK

ARTICLE INFO

Article history:
Received 17 February 2017
Received in revised form
4 April 2018
Accepted 18 April 2018
Available online 30 April 2018

Keywords:
Decision support systems
Semantic data
Ontology
ELECTRE
Electricity generation plants

ABSTRACT

Multi-Criteria Decision Aid methods are used to find the best option from a set of alternatives when multiple and conflicting criteria have to be optimized simultaneously. The evaluation of the suitability or risk of each alternative is usually performed by assigning a numerical value. However, sometimes the data required to measure a criterion may be found in the form of semantic values such as tags. This paper proposes a methodology to calculate the strength of an outranking relation for a pair of alternatives using semantic criteria following the principles of ELECTRE-III (i.e. by means of concordance and discordance indices). The preferences about semantic data are represented in an ontology by means of objective and subjective functions. The paper explains how this new methodology was applied to analyse different electricity generation technologies using environmental and economic criteria. Two scenarios are tested to show how semantic criteria may influence the final decision.

1. Introduction

The selection of the most suitable electricity generation plant is a very controversial topic worldwide that requires the analysis of multiple factors and the consultation of many stakeholders. For instance, the decision of the British government to build new nuclear power stations has received a lot of criticism since its approval in 2008 and has taken many years of amendments and debates until the first one, Hinkley Point C, was licensed in September 2016. There are many conflicting facts that need to be considered in order to find the most appropriate technologies for electricity production on each site. On the one hand, there is an increasing demand for energy. And, on the other hand, there is a great awareness for the need to protect the environment and reduce CO_2 emissions. In the literature, we can find several studies on sustainable energy production plants as a new means of generating energy while preserving the environment. The increase in concentration of atmospheric greenhouse gases (GHGs) due to the use of fossil fuels has led to the study of other energy supplies with lower GHG emissions and to the use of renewable resources.

For a complete evaluation of all the possible technologies, several indicators must be collected and properly analysed by taking into account the concerns and aims of the stakeholders involved in each particular case (i.e. the criteria used to evaluate the different alternatives will be very different in Iran, Japan or the UK). Fortunately, nowadays a lot of information and measures about the different characteristics of electricity generation plants is available and can be analysed to extract useful indicators that help to design decision support systems. For example, some data reports for several countries are available in public online data stores.

In these kinds of complex decision problems, multiple and conflicting criteria must be taken into account. *Multiple Criteria Decision Aiding* (MCDA) is a leading discipline that develops methods that help decision makers in the task of evaluating the different alternatives. There are three main approaches in MCDA: utility-based methods, outranking methods and rule-based methods (Figueira et al., 2005). This paper is focused on the ELECTRE outranking methods because of its high success in many domains (especially in ones related to energy and environmental assessment) (Papadopoulos and Karagiannidis, 2008; Georgopoulou et al., 1997). ELECTRE methods were proposed by Roy (Roy, 1996) and are based on finding a preference structure from the agreement of multiple criteria using a methodology that is inspired by social voting systems. Thus, this method is easily understood and accepted by decision makers. Different versions of ELECTRE can be found depending on the nature of the decision

* Corresponding author.
E-mail address: miriam.martinez@urv.cat (M. Martínez-García).

https://doi.org/10.1016/j.envsoft.2018.04.003
1364-8152/

problem to be solved (e.g. sorting, choice, ranking). ELECTRE methods have two main advantages in comparison with the other approaches: (1) they do not make strong assumptions on the preference between alternatives, and thus allow the decision maker to model preference uncertainties, and (2) they are characterized by the limited degree to which a disadvantage on a particular criterion may be compensated by advantages on other criteria, in comparison to utility methods that allow trade-offs among different criteria. In addition, the ELECTRE approach is very advantageous in applications where several stakeholders' views must be taken into account during the decision making process.

Current ELECTRE methods accept the evaluation of criteria with numerical and ordinal values. In this paper we present an extension of the ELECTRE-III method that works with *semantic* criteria, which may have tags (concepts) as values. The meaning of each tag depends on the domain and is represented in an ontology (Martínez-García et al., 2016; Valls et al., 2013). Ontologies are formal models of knowledge representation that include relations between concepts in taxonomies and can be used to store the user's preferences (Aldea et al., 2012; Valls et al., 2013). For the sake of clarity, we will refer to this new version as ELECTRE-III-SEM because it incorporates the semantic data values as novelty over the classic numerical approach. The aim of this paper is, hence, to show how the outranking method proposed in ELECTRE-III-SEM may be used to assess different types of power generation plants using both numerical and semantic data.

The rest of the paper is organized as follows. The following section reviews research carried out on the application of multi-criteria decision support systems in the domain of electricity generation technologies. Section 3 explains how the ELECTRE-III method builds an outranking relation that is used to rank the alternatives. Section 4 proposes an extension of ELECTRE-III to cater for multi-valued semantic criteria, which is the basis of the ELECTRE-III-SEM version. Section 5 is devoted to the assessment of several power generation technologies aimed to renovate the UK energy sector. Public data has been collected and analysed to make this study. The paper finishes with some conclusions and a discussion on the use of ELECTRE-III-SEM in other domains.

2. Related work

MCDA techniques have been applied in many domains as they can be utilised in complex decision-making processes in which multiple and conflicting criteria have to be analysed to identify the best option. That is the case when different electricity generation plants must be evaluated to select the option that satisfies the different criteria.

The criteria are classified in five main categories: environmental, economic, technological, political, and social (see (Wang et al., 2009) and (Strantzali and Aravossis, 2016)). Technological considerations include efficiency, safety, reliability and resource availability. The main economic criteria are the costs of investment, operation, maintenance and fuel. Environmental criteria comprise VOC, resource depletion, noise, and the emission of NO_X, CO_2, SO_2 and particulates. Social considerations include social acceptability, job creation and social benefits. Some papers give more importance to environmental and economic criteria and treat the others as complementary considerations (Ribeiro et al., 2013; Shmelev and Van Den Bergh, 2016; Hong et al., 2013).

Recent publications consider both renewable and non-renewable energies (Afgan and Carvalho, 2002; Stagl, 2006; Hunt et al., 2013; Shmelev and Van Den Bergh, 2016; Rovere et al., 2010; Stein, 2013; Chatzimouratidis and Pilavachi, 2008; Ribeiro et al., 2013; Stamford and Azapagic, 2014). In other studies, only renewable technologies are taken into consideration (Kaldellis et al., 2012; Papadopoulos and Karagiannidis, 2008; Georgopoulou et al., 1997; Haralambopoulos and Polatidis, 2003; Al Garni et al., 2016; Strantzali and Aravossis, 2016).

In all these studies, decision aid methods have been used to make an integrated analysis of the different energy generation technologies. Some approaches rely heavily on the knowledge and participation of a set of experts, such as the Delphi method (Kaldellis et al., 2012). In other papers, typical economic tools are used, for example the DEA method (Rovere et al., 2010). In the studies where MCDA methods are applied, the most common approach is based on utility theory, mainly using the Analytic Hierarchy Process (AHP) (Chatzimouratidis and Pilavachi, 2008). Outranking methods have also been explored, such as PROMETHEE (Haralambopoulos and Polatidis, 2003) and ELECTRE (Papadopoulos and Karagiannidis, 2008), but they are limited to numerical data, because they did not allow linguistic information until now.

The use of semantic information in decision support systems is an incipient research line. A common and successful way of introducing this kind of knowledge is using ontologies (Jakus et al., 2013). In (Valls et al., 2013) several ways of using the linguistic terms stored in an ontology for the description of objects are presented.

Another approach consists of using the ontology to represent the procedural and managerial information about a certain domain (i.e. tasks and their dependencies, requirements, resources, etc.). This latter approach is used for project management, strategic planning or to represent information and knowledge to facilitate system decision-making (Küçük and Arslan, 2014; Abanda et al., 2013) with renewable energy technologies.

Compendium (Shum et al., 2006) is a software tool based on the Issue Based Information System (IBIS) (Kunz and Rittel, 1970). Compendium allows information and ideas to be linked together through a visual interface. These concepts are expressed in the form of issues (question nodes), potential solutions (answer/position nodes) and arguments (pros and cons nodes). In OUTDO (Hunt et al., 2013), an extension of Compendium that encapsulates a MCDA is used (Aldea et al., 2012). The modified Compendium system supports the decision-making process by integrating a qualitative representation of the argumentation and rationale behind the different alternatives with quantitative criteria that evaluate them. The amended Compendium system, OUTDO (Hunt et al., 2013) was used to evaluate different electricity generation processes by considering diverse energy policies aimed to renovate the UK energy sector. The study focuses on nuclear power, coal with carbon capture and storage, and renewable energy generation. The case study described in this paper has been inspired by and is based on the study of UK power production plants developed by Hunt. The alternatives and some criteria have been taken from the case study developed in OUTDO. Semantic criteria have been added now using data available in public repositories, as they were not considered in the previous study. Moreover, in this paper an outranking-based approach is proposed, instead of a utility-based model as the one of OUTDO. Advantages of outranking methods, and ELECTRE in particular, have been previously recognized in the literature (Figueira et al., 2013). ELECTRE has 3 main advantages which are of interest in this study: different scales of measurement can be used without the need of a normalization pre-processing, compensation among criteria can be avoided with the veto power, and uncertainty in the performance comparison is managed by means of defining appropriate discrimination thresholds for each

criterion. ELECTRE has been already successfully used in other environmental problems where the ELECTRE model may capture the complexity of the decision requirements in this domain (Govindan and Jepsen, 2015)..

3. ELECTRE-III

This section describes the classic ranking method ELECTRE-III, which uses numerical and ordinal criteria. The following section will present its extension that is able to manage semantic multi-valued criteria.

The ELECTRE-III ranking method requires the following input data:

- Set of Alternatives, $A = \{a, b, c, d, \ldots\}$: it is the set of the n potential actions or solutions for the decision problem.
- Set of Criteria, $G = \{g_1, g_2, \ldots, g_m\}$: it contains a finite set of m numerical or ordinal indicators on which the alternatives are evaluated based on the goals of the decision maker.
- Vector of Weights, $\omega = \{w_1, w_2, \ldots, w_m\}$: every dimension w_j in the vector ω indicates the relevance or importance of the criterion on the final decision. W is the addition of all the weights, i.e. $\sum_{j=1}^{m} w_j = W$.

The ELECTRE outranking method builds a reflexive, non-transitive preference relation, S, between potential alternatives. Given two alternatives a and b, aSb means "a is at least as good as b", i.e. there are enough arguments to claim this statement and no argument refutes it.

ELECTRE-III constructs the outranking relation taking into account the uncertainty and imprecision associated to the pairwise comparison of the alternatives using pseudo-criteria. For this reason, each criterion is associated with the following two discrimination thresholds:

- Indifference threshold $q_j(a)$: given two alternatives a and b, it is the maximum difference of the scores on criterion g_j below which the decision maker is indifferent between both options.
- Preference threshold $p_j(a)$: given two alternatives a and b, it is the minimum performance difference of the scores on criterion g_j which implies a clear strict preference in favour of one alternative over another.

ELECTRE-III also includes the veto rule, which is the right of giving essential reasons for rejecting the outranking relation. This is introduced as another threshold:

- Veto threshold $v_j(a)$: given two alternatives a and b, a discordant difference of the scores larger than the veto in favour of b with respect to a in criterion g_j will require the negation of the outranking relation aSb (thus, if there is a criterion in which b is much better than a, it will not be possible to claim that a is at least as good as b).

Step 1. (construction of the outranking relation): The outranking relation S is built for each pair of alternatives $(a, b) \in AxA$ by comparing their performances on the set of criteria G. Alternative a outranks alternative b if, taking into account the preferences of the decision maker, a is at least as good as b and there is no strong argument against this claim. Two indices are applied to evaluate this relation: concordance and discordance. For each criterion $g_j \in G$, the *partial concordance* and *partial discordance* indices (c_j and d_j, respectively) are calculated as follows.

$$c_j(a,b) = \begin{cases} 1 & if \quad g_j(a) \geq g_j(b) - q_j(a) \\ 0 & if \quad g_j(a) \leq g_j(b) - p_j(a) \\ \dfrac{g_j(a) - g_j(b) + p_j(b)}{p_j(b) - q_j(b)} & otherwise. \end{cases} \tag{1}$$

$$d_j(a,b) = \begin{cases} 1 & if \quad g_j(a) \leq g_j(b) - v_j(a) \\ 0 & if \quad if\ g_j(a) \geq g_j(b) - p_j(a) \\ \dfrac{g_j(b) - g_j(a) - p_j(a)}{v_j(a) - p_j(a)} & otherwise \end{cases} \tag{2}$$

Notice that the threshold p_j is the one that determines if the output of the comparison of the performance of two alternatives is in favour of aSb or against it. The indifference and veto thresholds are used to determine the value of the concordance or discordance vote for a certain criterion.

The overall *concordance index* is computed for each pair of alternatives a, b using the voting power of each criterion, w_j, as:

$$c\,(a,b) = \frac{1}{W} \sum_{j=1}^{m} w_j c_j(a,b) \tag{3}$$

The overall concordance index and the partial discordance indices are used to calculate the degree of credibility of the outranking relation aSb, $\rho(a,b)$ as

$$\rho(a,b) = \begin{cases} c(a,b) & if\ \forall_j \ \ d_j(a,b) \leq c(a,b) \\ c(a,b).\prod_{j \in J(a,b)} \dfrac{1 - d_j(a,b)}{1 - c(a,b)} & otherwise \end{cases} \tag{4}$$

where $J(a,b)$ is the set of criteria for which the discordance is larger than the overall concordance.

Step 2. (distillation): The outranking relation is exploited to build a partial pre-order among the alternatives in A. It is an iterative process that selects a subset of alternatives at each step, given the credibility values of the outranking relation. This procedure yields two complete pre-orders (descending and ascending distillation chains), which are intersected to generate the final partial pre-order (Ishizaka and Nemery, 2013).

4. Managing semantic data with ELECTRE-III-SEM

The first simplified approach to the introduction of semantic data into ELECTRE was presented in (Martínez-García et al., 2016). That work showed a system that recommends touristic attractions by using semantic criteria for the different activities and weather conditions. In the present paper we introduce some modifications to that initial proposal, in order to increase the flexibility and generality of the method. With this extended methodology we can model and solve a more complex problem about assessment of power plant technologies where semantic data will be used to analyse two multi-valued semantic environmental criteria.

ELECTRE-III-SEM requires a domain ontology to represent the structure of the possible values of the semantic criteria. Every linguistic value (tag) that appears on the semantic criteria must appear as a concept in the corresponding ontology. The ontology also stores numerical preference scores on the concepts according

to the decision maker's goals, called "*Tag Interest Scores*" (TIS).

Therefore, a semantic user profile exists for each criterion, containing the user's degree of preference with respect to the domain concepts. This information may be exploited to compare and rank a set of alternatives.

In the ELECTRE-III-SEM procedure, alternatives will be evaluated with regards to a fixed set of numerical and semantic criteria. The decision procedure consists of the following steps (Fig. 1):

1. The decision maker constructs his ontology-based subjective semantic user profile.
2. The data matrix is collected with the objective information corresponding to each alternative and criterion.
3. The parameters of the method (discrimination thresholds and criteria weights) are set up by the decision maker.
4. Concordance and discordance indices are calculated and a final ranking procedure is applied to obtain a partial pre-order or a total ranking, which is presented to the decision maker.

The management of semantic criteria in ELECTRE-III-SEM version is similar to the one of numerical and ordinal criteria in ELECTRE-III. However, the concordance and discordance indices are now fuzzy functions defined in terms of the pairwise comparison of the Tag Interest Scores. This section explains how the concordance and discordance indices for semantic criteria are defined in terms of TIS by means of the Semantic Win Rate.

The TIS was originally defined in (Martínez-García et al., 2016) as a fixed numerical value for each tag t, so that it is denoted as $TIS(t)$. It can represent a gain goal (to maximize) or a cost goal (to minimize).

In this work we redefine and generalize this concept because in some decision problems the preference of a certain tag depends on the alternative to which the tag is associated. For example, a "sunny hot day" may be adequate for walking, but not for running. In that kind of situation, the TIS function needs to take into account not only the tag but also some information linked to the alternative, like its intensity. Therefore, we will now define a tag interest score function $TIS : T, A \rightarrow \mathbb{R}$ as:

$$TIS(t,a) = \rho_t(h_t(a)) \tag{5}$$

In this definition, $TIS(t,a)$ includes both subjective and objective information. For alternative a, $TIS(t,a)$ is defined in terms of a function $h_t : A \rightarrow \mathbb{R}$ for each tag t. Then, $h_t(a)$ is an objective measure of the quantity present in a of the concept represented by the semantic tag t, whereas ρ_t is a subjective evaluation function stored in

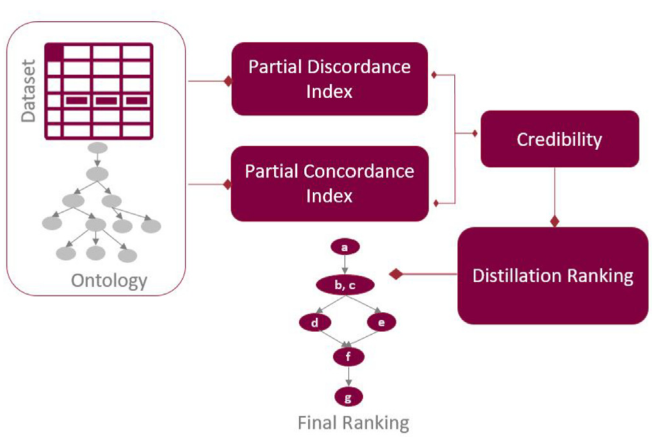

Fig. 1. Architecture of ELECTRE-III-SEM

the ontology that indicates the degree of preference on the calculated quantity of t on alternative a.

In order to measure the strength of the assertion aSb with respect to a multi-valued semantic criterion g_j, the *Semantic Win Rate* $SWR_j\ (a,b)$ is calculated. SWR is a numerical value in $[0,1]$ that indicates the degree of preference of alternative a with respect to b on the semantic criterion g_j. It is based on the two sets of tags $g_j(a) = \{t_{1,a}, t_{2,a}, \ldots, t_{|g_j(a)|,a}\}$ and $g_j(b) = \{t_{1,b}, t_{2,b}, \ldots, t_{|g_{j(b)}|,b}\}$.

Assuming that criterion g_j must be maximized, the Semantic Win Rate is calculated as follows:

$$\boldsymbol{SWR_j(a,b)} = \frac{\sum_{t_{i,a}} \sum_{t_{k,b}} \boldsymbol{f}(<\boldsymbol{t_{i,a}}, \boldsymbol{a}>, <\boldsymbol{t_{k,b}}, \boldsymbol{b}>)}{|\boldsymbol{g_j(a)}| \cdot |\boldsymbol{g_j(b)}|} \tag{6}$$

$$f(<x,a>, <y,b>) = \begin{cases} 1 & \text{if } TIS(x,a) \geq TIS(y,b) - q_j \\ 0 & \text{if } TIS(x,a) < TIS(y,b) - q_j \end{cases} \tag{7}$$

Thus, $SWR_j\ (a,b)$ is the proportion of tags on which a is at least as good as b when comparing against each other on the semantic criterion g_j. We introduce here an indifference threshold q_j similar to the one in standard ELECTRE, in order to define an interval of indistinguishability in regards to the TIS range of values.

The following examples of the calculation of SWR_j with two distinct values of indifference threshold show the influence of this parameter.

Example: consider two lists of pollutants produced by two different types of technologies, with their associated TIS value:

A (Radioactive 0.2, HumanHealth 0.9, GlobalWarm 0.4)
B (Radioactive 0.3, AirPollution 0.6, WaterPollution 0.2)

As the TIS value corresponds to the assessment of the risk associated to each tag and alternative, it must be minimized.

If we take $q_j = 0$, SWR_j (A,B) = 4/9 and SWR_j (B,A) = 6/9, so option B is preferable to A, because the pollutants in B have lower levels of risk.

Let us now introduce some indifference on the risk assessment value, with $q_j = 0.1$. Now, SWR_j (A,B) = 5/9 and SWR_j (B,A) = 7/9. This means that a risk 0.2 or 0.3 for the Radioactive tag is considered to be in the same level of preference, as well as the comparison of 0.4 and 0.3. Thus, the semantic win rate (SWR) changes, but option B is still better than A.

Using the SWR_j value, the partial concordance and partial discordance indices are defined as follows:

$$c_j(a,b) = \begin{cases} 1 & \text{if } SWR_j(a,b) \geq \mu_j \\ 0 & \text{if } SWR_j(a,b) \leq p_j \\ \dfrac{SWR_j(a,b) - p_j}{\mu_j - p_j} & \text{otherwise} \end{cases} \tag{8}$$

$$d_j(a,b) = \begin{cases} 1 & \text{if } SWR_j(a,b) \leq \nu_j \\ 0 & \text{if } SWR_j(a,b) \geq p_j \\ \dfrac{p_j - SWR_j\ (a,b)}{p_j - \nu_j} & \text{otherwise} \end{cases} \tag{9}$$

As $SWR_j(a,b)$ is an index that represents the comparison of the performance of a over b, the thresholds are not parameterised and have this meaning:

- μ_j is the strong threshold of the strength of $SWR_j(a,b)$ to consider maximum concordance with aSb.

- p_j is a weak threshold of the strength of $SWR_j(a,b)$ where the user may still have some preference of a with regards to b, thus still supporting the relation aSb to a certain degree.
- υ_j is the veto threshold, which is a value threshold below which $SWR_j(a,b)$ is low enough to imply the full discordance with the outranking relation.

In this case, the role of the thresholds is analogous to the one of the numerical case, p_j being the threshold that indicates if the value of the $SWR_j(a,b)$ is in favour of or against aSb, whereas μ_j and υ_j are used to determine the value of the concordance or discordance vote for a certain criterion. Notice that the following condition must hold: $\upsilon_j \leq p_j \leq \mu_j$.

5. Case study: energy generation

In this section the proposed ELECTRE-III-SEM procedure is applied to evaluate different methods to generate energy, taking into account environmental criteria related to the resources required to eliminate pollution and waste, and economic factors. A software tool has been constructed at University Rovira i Virgili to support the methodology proposed in this paper. The nine different alternatives (power generation plants) that have been taken into consideration are detailed in section 5.1. Each alternative has been evaluated in terms of five criteria considering the energy needs in the UK. Experts from Oxford Energy Network[1] have supervised the evaluation of the criteria. In this case study there are two semantic criteria (waste by-products and pollution-environmental damage) and the other three are numerical (energy source, economic cost of the electricity generation, and water usage). The aim is to identify the type of power generation plant that can best mitigate the effects it has on the environment. The final selection and definition of the set of criteria was based on the previous studies described in (Ribeiro et al., 2013; Hong et al., 2013; Shmelev and Van Den Bergh, 2016) and advice given by experts in the field. Accordingly, two dimensions were targeted: environmental risks and economic costs. The data of the indicators was extracted from public reports and databases. The construction of the criteria is explained in detail in the following subsections.

5.1. Technologies for energy generation

To preserve the environment and reduce CO_2 emissions, governments are considering the incorporation of renewable energy, nuclear plants and new technologies to counteract climate change. The different types of energy sources currently available are classified into non-renewable and renewable.

1. Non-renewable sources (Edenhofer et al., 2011), which have been used extensively until now, are nuclear fission, natural gas, and coal. One of the main disadvantages of coal power plants is the amount of pollution that the combustion of coal generates (NOX, CO2, and SO2). Nuclear power systems do not depend on renewable resources, but they reduce the consumption of fossil fuels (coal and oil) and have lower greenhouse gas emissions (CO2). However, nuclear waste is very radioactive, has a very long life span and is difficult to safely dispose of.
2. Renewable energy that comes from sources such as wind, geothermal heat, sun, sea and organic waste have become popular in the last decades. Wind power systems do not produce harmful emissions; moreover, they cause minor disruption to the environment and they do not depend on uranium or fossil fuels. Photovoltaic systems have many advantages as they do not produce dangerous emissions and they do not cause severe environmental impacts (Edenhofer et al., 2011). However, renewable energy sources are costly and have a lower energy density than non-renewable sources.

All of these methods have advantages and drawbacks making the decision hard. For this reason, the technologies and subcategories depicted in Table 1 have been analysed to decide the most suitable technology to generate electricity in an environmentally sustainable manner.

5.2. Numerical criteria

Three criteria have been evaluated numerically in this study: energy source, cost and water usage.

5.2.1. Energy source

Each of the alternatives has a single energy source, which has been obtained from the literature. It has been evaluated with a risk score between 0 (no risk to the environment) and 1 (highest risk to the environment) by a domain expert. The energy sources and their risk scores are shown in Table 2. This criterion has to be minimized in order to reduce the impact of the energy source on the environment.

5.2.2. Cost

This criterion evaluates the economic cost (£/Mwh) of generating energy for each alternative. Table 3 lists the cost for each of them, obtained from the database published in (National Renewable Energy Laboratory, 2015), which includes the costs of operation, fuel and maintenance through Levelized Cost of Energy (LCOE).

5.2.3. Water usage

In this study we have considered water usage as the water consumption for the full life cycle stages including the fuel management (its extraction, processing and transportation) and the power plant life cycle (component manufacturing, power plant construction, power plant decommissioning and power plant operation). In addition, we have taken into account that each power generation technology may use a different cooling system. Then, we have considered cooling towers for NCL, NGCC, IGCC, PC and BIO, dry cooling for GEO, and no cooling system in the case of HY, Wind and SP. The water usage (litres/MWh) reported in Table 3 was obtained from (Meldrum et al., 2013; Macknick et al., 2011).

5.3. Semantic criteria

The semantic criteria considered in this study are *Waste By-*

Table 1
Energy generation technologies.

Renewable	Sub-category
Solar Photovoltaic	Concentrated Photovoltaic (SP)
Wind	Offshore (WO)
Hydropower	Conventional-Aggregated In-Stream and Reservoir (HY)
Geothermal	Enhanced (GEO)
Biopower (BIO)	
Non-renewable	
Natural Gas Combined Cycle (NGCC)	
Integrated Coal Gasification Combined (IGCC)	
Nuclear Power (NCL)	
Pulverized Coal (PC)	

[1] http://www.energy.ox.ac.uk/wordpress/.

Table 2
Values of the Energy Source criterion.

Alternatives	Energy Source	Score
NCL	Uranium-U	0.9
NGCC	Shale Gas	0.5
IGCC	Bituminous Coal	0.3
PC	Lignite Coal	0.3
BIO	Energy Crop	0.2
GEO	Geothermal Heat	0.1
WO	Wind	0
SP	Solar Radiation	0
HY	Water	0

Table 3
Economic and water usage cost of energy generation.

Alternatives	Cost (£/Mwh)	Water Usage (litres/MWh)
NCL	100.19	2725.50
NGCC	61.66	794.93
IGCC	131.02	1211.33
PC	115.61	2006.27
BIO	84.78	2093.33
GEO	100.19	3217.60
WO	154.14	3.78
SP	196.68	113.56
HY	77.07	17000.28

Products and *Pollution Environmental Damage.* The criterion *Waste By-Products* describes the different contaminating substances that are produced by each of the alternative ways of generating energy (e.g. radioactive waste or CO_2). The criterion *Pollution Environmental Damage* shows different kinds of pollution (e.g. on air, water, soil) and some of its pernicious effects (e.g. acid rain, global warning).

These criteria are multi-valued; therefore each alternative has a list of tags for each of them. These tags are the leaves of the domain ontology shown in Fig. 2. This ontology was constructed using information from the OUTDO framework and the participation of domain experts (Hunt et al., 2013).

In order to evaluate each alternative using these semantic tags, a numerical measure has to be assigned to each tag in the ontology. As proposed before, each leaf a of the ontology stores a function called $TIS(t, a)$ defined in Eq. (5). It assigns a risk value to each tag t and technology type a depending on the associated numerical measurement $h(a)$. The risk functions have been set using information from the literature and the domain knowledge of the experts on our team.

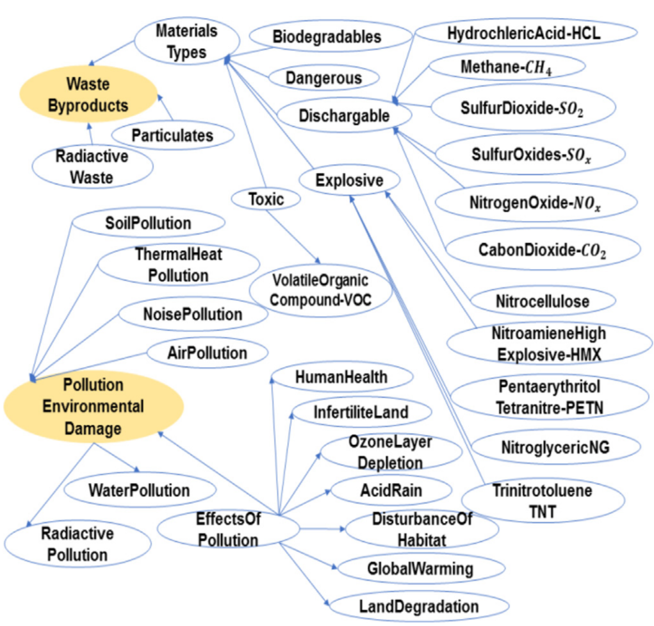

Fig. 2. Ontology for semantic criteria.

5.3.1. Calculating the TIS value on each tag of the ontology

First, the measurements of each indicator have been extracted from different databases. Table 4 shows the emissions of non-renewable (NGCC, IGCC, PC) and biopower technologies for the criterion *waste by-products*, taken from (Cai et al., 2012; Köppen et al., 2014).

To assign a TIS to each of the tags for each alternative, the ranges of g/kWh emissions were discretised and a risk score was assigned to each interval with the help of an expert's knowledge. The intervals and scores of these by-products are given in Table 5.

The TIS score of the tags assigned to the two semantic attributes for every alternative is shown in Table 6. For the tags that do not appear in the table, the TIS is considered to be zero because they are not by-products obtained by the corresponding power plant technology.

In some cases the tag is listed even though the TIS is 0. This is the case of some energy renewable technologies (GEO, WO, SP and HY), where the quantities of by-product emissions exist but are negligible. In this case, experts explicitly put the tag but a null risk is considered (TIS = 0).

The tags of the pollutants (and their respective TIS) of the *Pollution Environmental Damage* criterion were assigned by an expert. Again, in renewable technologies we find tags such as "Noise Pollution", "Land Degradation", "Disturbance of Habitat" with low risk scores (TIS = 0.1), in the cases of WO, SP and HY. Similarly, to the other criterion, a null TIS is considered when the tag is not explicitly indicated in the table. Those kinds of power plants generate minimum pollution or environmental damage during their operation processes.

The five criteria explained in this section will be used to compare the set of nine power plants. These criteria represent two main issues that are important for the selection of the best plant: amount of resources required (money and water) and environmental impact of the source type (the generated waste and pollution). In the following section, the proposed ELECTRE-III-SEM procedure will be used to obtain a ranking of the power plants using this information.

6. Evaluation using ELECTRE-III-SEM

The ELECTRE-III-SEM procedure proposed in this paper was evaluated by setting different configurations to the parameters in the case study. Two tests were performed and evaluated:

- In Test 1, the influence on the ranking of the preference and veto thresholds was analysed in order to study the sensibility of the ranking result to these parameters. For numerical criteria, two scenarios were designed: one with veto power in all criteria and

Table 4
By-product emissions for different kinds of power plants, in g/kWh.

Alternatives	CO_2	NO_X	SO_X	CH_4	VOC
NGCC	408.7	0.0629	0.0020	0.0079	0.0017
IGCC	716.6	0.2150	0.044		
PC	1003.4	0.94548	2.4057	0.0116	0.0086
BIO	0.0	0.078	0.322		0.070

Table 5
Intervals for the waste by-products.

CO_2 (t)		NO_X (t)		SO_X (t)		CH_4 (t)		VOC (t)	
0–100	0.1	0–0.05	0	0–0.1	0	0–0.002	0		0
100–200	0.2	0.05–0.08	0.1	0.01–0.04	0.1	0.002–0.003	0.1		0.1
200–300	0.3	0.08–0.09	0.2	0.04–0.05	0.2	0.003–0.004	0.2	0.001–0.005	0.2
300–400	0.4	0.09–0.1	0.3	0.3–0.8	0.3	0.004–0.005	0.3	0.005–0.1	0.3
400–500	0.5	0.1–0.2	0.4	0.8–1.00	0.4	0.005–0.006	0.4		0.4
500–600	0.6	0.2–0.3	0.5	1.00–1.20	0.5	0.006–0.007	0.5		0.5
600–700	0.7	0.3–0.4	0.6	1.20–1.50	0.6	0.007–0.008	0.6		0.6
700–800	0.8	0.4–0.5	0.7	1.50–2.00	0.7	0.008–0.02	0.7		0.7
800–1100	0.9	0.5–1	0.8	2.00–2.50	0.8	0.02–0.03	0.8		0.8
1100–1300	1	1–2	0.9	2.5–3.00	0.9	0.03–0.04	0.9		0.9
		2–3	1	3.00–4.00	1	0.04–0.05	1		1

Table 6
Tag interest scores (risk) for the values of the semantic criteria for each alternative.

Alternative	Waste-Byproducts TIS		Pollution-EnviorionmentalDamage TIS	
NCL	RadioactiveWaste	1	RadioactivePollution	0.8
			WaterPollution	0.8
NGCC	CO_2	0.5	AirPollution	0.4
	SO_X	0.1	GlobalWarming	0.3
	NO_X	0.1	HumanHealth	0.4
	CH_4	0.6		
	VOC	0.2		
IGCC	CO_2	0.8	AirPollution	0.6
	SO_X	0.2	GlobalWarming	0.7
	NO_X	0.5	HumanHealth	0.6
PC	CO_2	0.9	AirPollution	0.8
	SO_X	0.8	GlobalWarming	0.7
	NO_X	0.8		
	CH_4	0.7	HumanHealth	0.7
	VOC	0.3	AcidRain	0.8
BIO	SO_X	0.3	AirPollution	0.1
	NO_X	0.1	GlobalWarming	0.2
	VOC	0.3		
	Biodegradables	0.1		
GEO	SO_2	0.1	AirPollution	0.3
	NO_X	0.1	GlobalWarming	0.1
	Particulates	0		
	NMVOC	0		
WO	SO_2	0	NoisePollution	0.1
	NO_X	0		
	Particulates	0		
	NMVOC	0		
SP	SO_2	0	LandDegradation	0.1
	NO_X	0		
	Particulates	0		
	NMVOC	0		
HY	SO_2	0	DisturbanceOfHabitat	0.1
	NO_X	0		
	Particulates	0		

the other without veto power for the numerical features. In the second scenario, numerical criteria may be compensated by good performance in semantic criteria, but not the other way round. This scenario enables the detection of the compensation effects between different types of criteria.

- Test 2 aims to evaluate the degree to which the decision process was affected by the weighting power given to different subsets of criteria. Cases with and without veto power were compared to see how the veto may change the final ranking in criteria with low weight. In this test, two groups of criteria were defined, each one containing criteria of the two types. Therefore, we can analyse the influence of the criteria in the final ranking under different weight conditions, regardless of their type.

In all tests, indifference thresholds q_j were fixed to 0.1 for the semantic criteria and 0 for numerical ones. For the semantic criteria we also fixed $\mu_j = 0.7$.

6.1. TEST 1: sensitivity to preference and veto

The first test studies the influence of the preference threshold p_j (with values 0.5, 0.3 and 0.1) on semantic criteria. Thus, the veto threshold is fixed to the maximum possible veto value (which means low discordance effect) for all criteria. This corresponds to $v_j = 0.7$ for semantic data (v^s), and v^n is equal to g_j for numerical criteria. The preference threshold of numerical data is fixed to 20% of the range of g_j. All criteria have the same weight.

Fig. 3 shows the rank position (1 being the best) of each alternative. On the left ($v^n = 70\%$) we have the three rankings for different values of p_j and the veto power in all criteria. On the right (no v^n) we excluded the discordance step in the numerical criteria (i.e. veto was avoided), so only semantic ones may be in discordance.

Biopower and Wind have the same ranking for all the settings in Fig. 3, so their two lines overlap. Thus, the best energy sources are always Biopower, Wind and Geothermal. NGCC is ranked after them in the scenarios with veto of the numerical criteria, but it is

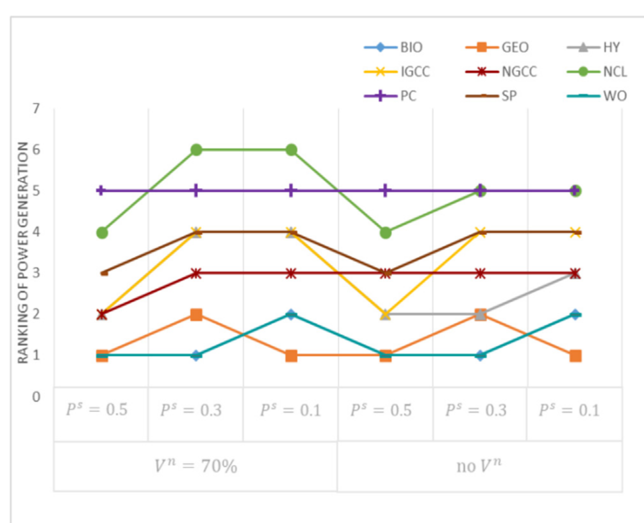

Fig. 3. Results of Test 1 in two scenarios: with veto in numerical criteria (left), without veto for numerical criteria (right).

outperformed by Hydropower when veto is not considered. Conversely, the worst power generation plants for the given criteria are Pulverized Coal and Nuclear. Nuclear power plants are worse than Pulverized Coal when numerical criteria apply veto and the preference threshold is low. Thus, given the criteria used, our method clearly identifies that renewable energy sources outperform the non-renewable ones.

From the previous tables, we can observe that Geothermal is preferable to Biopower regarding the *Waste-By-Products* criterion, but it is worse in terms of environmental pollution (*Pollution-Environmental Damage)* in the semantic criteria. Furthermore, for the numerical criteria, Geothermal technology is preferable as *Source Energy* but it is the most expensive and requires more water. Consequently, depending on the parameters, GEO and BIO exchange the two first positions in the ranking. Hydropower is one of the alternatives that suffers stronger changes of position in the ranking. In addition, Hydropower technology is among the best alternatives for low p_j values (strict configuration) but this alternative is very sensitive to changes in tolerance.

ELECTRE-III-SEM also generates a partial pre-order graph. Fig. 4 depicts the results of Test 1 for the case of $p^S = 0.5$ with veto in all criteria (left graph) and with no veto for water usage and source type (right graph). Three options are placed in the top positions: Biopower and Geothermal are indifferent, while Wind is incomparable to them (no one is preferred to the other). Wind as a source of energy is expensive but it does not consume water and it has very low contamination values. On the other hand, Biopower and Geothermal are much cheaper energy sources and they have few waste by-products, but they require some water. Therefore, BIO and GEO outperform Wind in costs but Wind is preferable if water consumption and waste are taken into consideration. Overall, the three of them outrank the remaining alternatives. We can also see that Hydropower is incomparable to many other alternatives. These situations of incomparability of the attributes can only be seen in the graphic of the preorder, which is a useful output of this method. A clear preference is always found between IGCC, NCL and PC. Those preference relations may also be useful for the decision maker to make the most convenient selection.

6.2. TEST 2: sensitivity to weights on criteria

This test uses the same values as test 1 for the q^n, q^s, v^n, v^s thresholds. A strict preference setting was decided ($p^n = 20\%$, $p^s = 0.5$). In this test, we study the results obtained by changing the weight of two groups of criteria - Group A: *energy source* and *water usage* and Group B: *waste by-products*, *pollution-environmental damage* and *cost.* A difference of five times is considered, which means that one group of criteria will have five times more voting power than the other group (when calculating concordance). In Case 1, the weight of Group A is 1 and B's weight is 5, whereas the weights are reversed in Case 2. In this test, we compare three situations: first, all criteria have a veto threshold, second, semantic criteria cannot veto (avoid sem) and third, numerical criteria cannot veto (avoid num).

Fig. 5 shows the ranking positions, although some alternatives are hidden because they have the same rank. When semantic information and cost have a larger weight (Case 1), the best options are Biopower and Geothermal. When we decrease the importance of these criteria and increase the weight of water usage and energy source (Case 2), the winner is clearly the Wind power, followed in second position by Biopower and Solar Photovoltaic, which outperform Geothermal. In general, non-renewable technologies are found in the last positions, except NGCC.

It can be observed that, in the first case, Wind descends positions when numerical criteria do not veto the outranking relation. Wind is one of the best in terms of energy source and water usage, but in Case 1 these two criteria have a low weight, and therefore the only way to influence the ranking result is by vetoing Group A. When we do not allow the veto power for those criteria, they are almost neglected in the calculation of the ranking, thus Wind goes from the second position to the third. Oppositely, Hydropower improves its position when numerical criteria do not veto because then it is not penalized by its large requirement of water.

In Case 2, we can see that Solar Photovoltaic technology is considered among the best options because we are giving more importance to energy sources and water usage (Group A). Significant differences in rank positions can be found when changing the balance of the criteria in favour of one or another set (see for example the rankings of Hydropower, Geothermal and Nuclear). For instance, Hydropower moves from the first position in Case 1 to the fourth position in Case 2. Moreover, we notice that non-renewable technologies are always in the last positions. Nuclear technology also has a significant change in positions in the two cases. In Case 1, IGCC and PC are worse than Nuclear but, in Case 2, Nuclear becomes the worst, together with Pulverized Coal.

Despite the differences found in the different tests, Wind power and Biopower are always in the top positions. According to (Carvalho et al., 2012), wind power is growing due to the increasing prevalence of wind-generated electricity in many countries. These results coincide with the recommendation to use renewable power technologies.

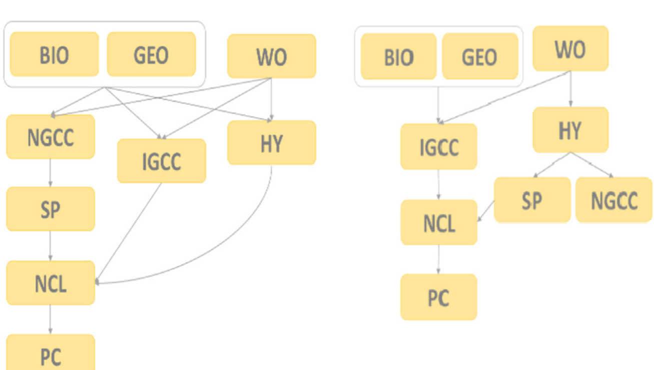

Fig. 4. Partial pre-orders obtained for Test 1 when using a preference threshold of 0.2, in two scenarios: with veto in numerical criteria (left), without veto for numerical criteria (right).

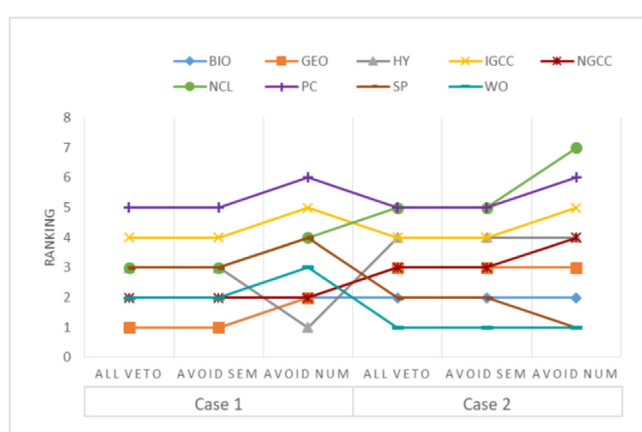

Fig. 5. Results for Test 2 considering different weights on two groups of criteria.

The analysis done in this section is highly sensitive to each country, both in the semantic and quantitative variables. For example, costs may be different in other locations. Regarding the semantic criteria, although the tags will be the same all around the world (because pollutants and waste depends on the technology type and not on the location), the subjective evaluation of risks may be different depending on the conditions of each place. Moreover, the parameters used in the model (thresholds, veto power, weights) also greatly depend on the expert's requirements.

7. Conclusions

In this paper, we have proposed a decision aiding method that is able to analyse numerical and linguistic data, which is an extension of the classical ELECTRE-III ranking method. The management of linguistic data is based on the Semantic Win Rate, a new measure that permits the comparison of pairs of alternatives according to the decision maker's preferences. The semantic interpretation of the tags and the initial preference values are stored in a domain ontology. This methodology has been applied to a case study that aims to assess different energy generation technologies with the purpose of renovating the UK energy sector. Results show that if only criteria related to environmental aspects and economic cost of energy sources are taken into consideration, the power plants that use renewable energy are preferable to those based on non-renewable sources of energy. In particular, for the case of UK, Wind and Biomass power plants are the ones suggested by the system for being the most environmentally sustainable and cheaper to maintain.

Until now, the majority of the MCDA methods have been designed to work with numerical indicators, but this situation is changing. Nowadays, it is possible to find linguistic information about the elements that are being analysed, such as the tags used in this paper (e.g. by-products). Excluding this information from the analysis may lead to errors or to a biased result due to the lack of important indicators. Therefore, ELECTRE-III-SEM is a promising tool that works with qualitative information. In this method, the key components that are needed are a domain ontology and the preference functions that measure the performance of each tag for each alternative. However, this kind of knowledge may be difficult to formalise in some domains. In this paper, we have obtained this preference function from an analysis of the numerical measurement of each tag for each alternative. There are several new preference learning techniques that are being developed and could also be used if sufficient historical data is available (Fürnkranz and Hüllermeier, 2010). Data mining tools will play here an important role and the combination of data mining with MCDA methods (like ELECTRE) is a promising research line, as it has already been shown in some recent works in environmental applications (Erener et al., 2016; Kadziński et al., 2018).

This method for decision support can be used in many other domains. Currently, thanks to new software tools and the easy availability and accessibility of large datasets of information, the collection and automatic pre-processing of information that is required to evaluate criteria is much easier than some decades ago. An interesting further work would be to use these datasets to evaluate different conditions and analyse how decisions are affected by changes in those conditions.

Acknowledgments

This work has been funded by the Spanish research project SHADE (TIN-2012-34369). This article has been possible with the support of Universitat Rovira i Virgili (2017PFR-URV-B2-61). The first author is supported by a research grant Martí Franquès of Universitat Rovira i Virgili (2014PMF-PIPF-70). The first author also wants to thank Oxford Brookes University for inviting her to a research stay and the researchers at the Department of Engineering Science at Oxford University for helping her to develop the case study.

References

Abanda, F.H., Tah, J.H.M., Duce, D., 2013. PV-TONS: a photovoltaic technology ontology system for the design of PV-systems. Eng. Appl. Artif. Intell. 26 (4), 1399–1412.
Afgan, N.H., Carvalho, M.G., 2002. Multi-criteria assessment of new and renewable energy power plants. Energy 27 (8), 739–755.
Al Garni, H., Kassem, A., Awasthi, A., Komljenovic, D., Al-Haddad, K., 2016. A multicriteria decision making approach for evaluating renewable power generation sources in Saudi Arabia. Sustain. Energy Technol. Assess. 16, 137–150.
Aldea, A., Bañares-Alcántara, R., Skrzypczak, S., 2012. Managing information to support the decision making process. J. Inf. Knowl. Manag. 11 (3), 1.
Cai, H., Wang, M., Elgowainy, A., Han, J., 2012. Updated Greenhouse Gas and Criteria Air Pollutant Emission Factors and Their Probability Distribution Functions for Electric Generating Units. Report of Argonne National Laboratory, U.S. Department of Energy, Chicago, Illinois.
Carvalho, D., Rocha, A., Gómez-Gesteira, M., Santos, C., 2012. A sensitivity study of the WRF model in wind simulation for an area of high wind energy. Environ. Model. Software 33, 23–34.
Chatzimouratidis, A.I., Pilavachi, P.A., 2008. Sensitivity analysis of the evaluation of power plants impact on the living standard using the analytic hierarchy process. Energy Convers. Manag. 49 (12), 3599–3611.
Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Seyboth, K., Eickemeier, P., Matschoss, P., Von Stechow, C., 2011. IPCC, 2011: summary for policymakers. In: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. Cambridge University Press.
Erener, A., Mutflu, A., Düzgün, S., 2016. A comparative study for landslide susceptibility mapping using GIS-based multi-criteria decision analysis (MCDA), logistic regression (LR) and association rule mining (ARM). Eng. Geol. 203, 45–55.
Figueira, J.R., Greco, S., Ehrgott, M., 2005. Multiple Criteria Decision Analysis: State of the Art Surveys. Springer.
Figueira, J.R., Greco, S., Roy, B., Słowiński, R., 2013. An overview of ELECTRE methods and their recent extensions. J. Multi-Criteria Decis. Anal. 20, 61–85.
Fürnkranz, J., Hüllermeier, E., 2010. Preference Learning. Springer-Verlag.
Georgopoulou, E., Lalas, D., Papagiannakis, L., 1997. A multicriteria decision aid approach for energy planning problems: the case of renewable energy option. Eur. J. Oper. Res. 103 (1), 38–54.
Govindan, K., Jepsen, M.B., 2015. ELECTRE: a comprehensive literature review on methodologies and applications. Eur. J. Oper. Res. 250, 1–29.
Haralambopoulos, D.A., Polatidis, H., 2003. Renewable energy projects: structuring a multi-criteria group decision-making framework. Renew. Energy 28 (6), 961–973.
Hong, S., Bradshaw, C.J.A., Brook, B.W., 2013. Evaluating options for the future energy mix of Japan after the Fukushima nuclear crisis. Energy Pol. 56 (March 2011), 418–424.
Hunt, J.D., Bañares-Alcántara, R., Hanbury, D., 2013. A new integrated tool for complex decision making: application to the UK energy sector. Decis. Support Syst. 54 (3), 1427–1441.
Ishizaka, A., Nemery, P., 2013. Multi-criteria Decision Analysis: Methods and Software. John Wiley & Sons.
Jakus, G., Milutinović, V., Omerović, S., Tomažič, S., 2013. Concepts, Ontologies, and Knowledge Representation. Springer-Verlag.
Kaldellis, J.K., Anestis, A., Koronaki, I., 2012. Strategic planning in the electricity generation sector through the development of an integrated Delphi-based multi-criteria evaluation model. Fuel 106, 212–218.
Kadziński, M., Cinelli, M., Ciomek, K., Coles, S.R., Nadagouda, M.N., Varma, R.S., Kirwan, K., 2018. Co-constructive development of a green chemistry-based model for the assessment of nanoparticles synthesis. Eur. J. Oper. Res. 264, 472–490.
Köppen, S., Fehrenbach, H., Markwardt, S., Hennecke, A., Eppler, U., Fritsche, U., 2014. Implementing the GBEP Indicators for Sustainable Bioenergy in Germany. Report from IINAS and IFEU, Heidelberg, Darmstadt, Berlin, Germany.
Küçük, D., Arslan, Y., 2014. Semi-automatic construction of a domain ontology for wind energy using Wikipedia articles. Renew. Energy 62, 484–489.
Kunz, W., Rittel, H., 1970. Issues as Elements of Information Systems. Center for Planning and Development Research, University of California at Berkeley.
Macknick, J., Newmark, R., Heath, G., Hallett, K.C., 2011. A Review of Operational Water Consumption and Withdrawal Factors for Electricity Generating Technologies. National Renewable Energy Laboratory, U.S. Department of Energy, Golden, Colorado.
Martínez-García, M., Valls, A., Moreno, A., 2016. Construction of an outranking relation based on semantic criteria with ELECTRE-III. In: Information Processing and Management of Uncertainty in Knowledge-based Systems Part II, vol. 611. Springer, pp. 238–249.
Meldrum, J., Nettles-Anderson, S., Heath, G., Macknick, J., 2013. Life cycle water use

for electricity generation: a review and harmonization of literature estimates. Environ. Res. Lett. 8, 015031.

National Renewable Energy, 2015. Website Open Energy Information. http://en.openei.org/apps/TCDB/.

Papadopoulos, A., Karagiannidis, A., 2008. Application of the multi-criteria analysis method Electre III for the optimisation of decentralised energy systems. Omega 36 (5), 766–776.

Ribeiro, F., Ferreira, P., Araújo, M., 2013. Evaluating future scenarios for the power generation sector using a Multi-Criteria Decision Analysis (MCDA) tool: the Portuguese case. Energy 52, 126–136.

Rovere, E.L., La Soares, J.B., Oliveira, L.B., Lauria, T., 2010. Sustainable expansion of electricity sector: sustainability indicators as an instrument to support decision making. Renew. Sustain. Energy Rev. 14 (1), 422–429.

Roy, B., 1996. Multicriteria Methodology for Decision Aiding. Kluwer Academic Publischers, Dordrecht.

Shmelev, S.E., Van Den Bergh, J.C.J.M., 2016. Optimal diversity of renewable energy alternatives under multiple criteria: an application to the UK. Renew. Sustain. Energy Rev. 60, 679–691.

Shum, S.J., Selvin, A.M., Sierhuis, M., Conklin, J., Haley, C.B., Nuseibeh, B., 2006. Hypermedia support for argumentation based rationale: 15 years from gIBIS and QOC. Ration. Manag. Software Eng. 111–132.

Stagl, S., 2006. Multicriteria evaluation and public participation: the case of UK energy policy. Land Use Pol. 23 (1), 53–62.

Stamford, L., Azapagic, A., 2014. Life cycle sustainability assessment of UK electricity scenarios to 2070. Energy Sustain. Dev. 23, 194–211.

Stein, E.W., 2013. A comprehensive multi-criteria model to rank electric energy production technologies. Renew. Sustain. Energy Rev. 22, 640–654.

Strantzali, E., Aravossis, K., 2016. Decision making in renewable energy investments: a review. Renew. Sustain. Energy Rev. 55, 885–898.

Valls, A., Moreno, A., Borràs, J., 2013. Preference representation with ontologies. In: Multicriteria Decision Aid and Artificial Intelligence. John Wiley & Sons, pp. 77–99.

Wang, J.-J., Jing, Y.-Y., Zhang, C.-F., Zhao, J.-H., 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. A review. Renew. Sustain. Energy Rev. 13 (9), 2263–2278.